Dynamic connectedness and integration among large cryptocurrencies

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Abstract

This study applies a set of measures developed by Diebold and Yilmaz (2012, 2016) to examine connectedness via return and volatility spillovers across six large cryptocurrencies from August 7, 2015 to February 22, 2018. Regardless of the sign of returns, the results show that Litecoin is at the centre of the connected network of returns, followed by the largest cryptocurrency, Bitcoin. This finding implies that return shocks arising from these two cryptocurrencies have the most effect on other cryptocurrencies. Further analysis shows that connectedness via negative returns is largely stronger than via positive ones. Ripple and Ethereum are the top recipients of negative-return shocks, whereas Ethereum and Dash exhibit very weak connectedness via positive returns. Regarding volatility spillovers, Bitcoin is the most influential, followed by Litecoin; Dash exhibits a very weak connectedness, suggesting its utility for hedging and diversification opportunities in the cryptocurrency market. Taken together, results imply that the importance of each cryptocurrency in return and volatility connectedness is not necessarily related to its market size. Further analyses reveal that trading volume and global financial and uncertainty effects as well as the investment-substitution effect are determinants of net directional spillovers. Interestingly, higher gold prices and US uncertainty increase the net directional negative-return spillovers, whereas they do the opposite for net directional positive-return spillovers. Furthermore, gold prices exhibit a negative sign for net directional-volatility spillovers, whereas US uncertainty shows a positive sign. Economic actors interested in the cryptocurrency market can build on our findings when weighing their decisions.

Keywords: Cryptocurrencies; market integration; return and volatility connectedness networks; asymmetric spillover.

JEL classification: C52, G11, G17.

1. Introduction

The cryptocurrency market has quickly become an important element of the global financial market (Gajardo et al., 2018) and a new asset class (Corbet et al., 2018). It has seen exponential growth in both market value and number of digital coins, growing from around $17.7 billion in market value at the start of 2017 to more than $700 billion in early 2018[1]. Importantly, newly introduced cryptocurrencies such as Ethereum, Ripple, Litecoin, Stellar and Dash are gradually cutting into Bitcoin's historically dominant market-value share,[2] suggesting that investors are taking a breather from Bitcoin and looking at alternative cryptocurrencies. The latter, which have generally borrowed some concepts and technological elements (e.g., blockchain technology) from Bitcoin, have recently attracted much attention and created tremendous opportunities for cryptocurrency investors to maximize returns. This is not surprising, given that each of these alternative cryptocurrencies outperformed Bitcoin in 2017, delivering astonishing returns ranging from 5000% (Litecoin) to 36 000% (Ripple) as compared to the 1300% price appreciation in Bitcoin. In addition to a middle group of individual investors who consider cryptocurrency-related investment, fund managers have been viewing cryptocurrencies as an investable asset class capable of generating high returns despite their extreme volatility.

Surprisingly, the growing interest in alternative cryptocurrencies for investment purposes is still accompanied by a limited understanding of how leading cryptocurrencies – with a market value exceeding 10 billion USD and relatively high liquidity – interact with one another in terms of return and volatility. In fact, the short history of the cryptocurrency market has shown some relative heterogeneity among leading cryptocurrencies in terms of returns, volatility and market value.[3] Extending the limited literature on dynamic connectedness and integration in cryptocurrency markets would help crypto-investors in devising investment and trading strategies that may involve combining leading cryptocurrencies within the same portfolio. Accordingly, the aim of this study is to examine

[1] Notably, since that peak, the cryptocurrency market lost most of its upside momentum and its value tumbled by more than 70% by mid-2018.

[2] Bitcoin's market value accounted for more than 85% of the total cryptocurrency market in the first quarter of 2015. Since then, it has seen a significant drop in its market share, falling to 39% at the end of 2017. In contrast, Ethereum has become the second-largest cryptocurrency, accounting for 15% of the total cryptocurrency market. At the end of 2017, the combined market value of Ethereum, Ripple, Litecoin, Stellar and Dash is slightly shy of Bitcoin's market value.

[3] It is intuitive that Litecoin, a fork of Bitcoin launched in in 2011, should have a close relationship with Bitcoin.

connectedness via return and volatility spillovers across large cryptocurrencies using a set of measures developed by Diebold and Yilmaz (2012, 2016). In doing so, we differentiate between positive and negative returns. We also consider the determinants of net directional return and volatility spillovers.

Generally, building network connectedness among price returns and volatility is hardly new in conventional assets such as equities (e.g., Fowowe and Shuaibu, 2016; Shahzad et al., 2018) and bonds (Louzis, 2015; Ahmad et al., 2018). Interestingly, it helps in understanding stress periods (i.e. financial and economic crises) and their propagation mechanisms as well as in identifying systemic risk (Louzis, 2015). In terms of implications, the construction of network connectedness helps policy-makers in formulating their policies that consist in preserving financial stability. Investors and risk managers can also benefit from building network of connectedness across asset classes to adjust their investment and hedging decisions. Prior studies have uncovered the network of connectedness among and within different assets/markets that include equities (Fowowe and Shuaibu, 2016; Shahzad et al., 2018; Zhang et al., 2018), bonds (Louzis, 2015; Ahmad et al., 2018), currencies (Baruník, et al., 2017; Singh et al., 2018), commodities (Ji et al., 2018a & b; Zhang and Broadstock, 2018), and interest rates (Louzis, 2015). Generally, empirical evidence suggests that connectedness in both return and volatility is significant, time-varying, and is shaped by crisis periods (Shahzad et al., 2018; Zhang and Broadstock, 2018). Importantly, the related literature often finds that the largest stock market such as the US is the largest transmitter of shocks to the stock markets of developed and emerging markets (e.g., Candelon et al., 2018). Quite similar results are reported for the case of bonds (Ahmad et al., 2018). Furthermore, connectedness among price returns and volatility intensifies during crises periods, leading to contagion that jeopardizes the stability of the financial system and to less possibilities for portfolio diversification.

However, the network of connectedness is extremely understudied in the cryptocurrency market that becomes an appealing investment ground for investors. Surprisingly, there is still a lack of understanding of the return and volatility spillovers among leading cryptocurrencies and that for the sake of risk management and portfolio diversification. Specifically, understanding the spillovers among cryptocurrencies provides useful information regarding investment and hedging decisions. For example, investors can exploit evidence of weak connectedness across cryptocurrencies to maximize diversification opportunities or hedging strategies. An investigation by Corbet et al. (2018) is among the rare studies that examine network connectedness involving the Bitcoin market.[4] Our study differs in several ways. Most notably, we not only study aggregate returns but are interested in asymmetric connectedness between positive- and negative-return spillovers. This allows us to highlight the relative importance of negative and positive shocks to each of the cryptocurrencies under study. Further on, we compute daily volatility and then investigate volatility connectedness among cryptocurrency markets, which makes our analysis the first to provide findings on the dynamic volatility spillover of the six leading cryptocurrencies, which account for more than 72% of the cryptocurrency market's value. Accordingly, our larger dataset and a refined methodology that differentiates between the connectedness of positive and negative returns make our analysis highly informative to market participants interested in the diversification potential among the largest cryptocurrencies, which are also the most liquid. Finally, we explore several factors as determinants of total and net directional spillovers by considering various market conditions and market-development characteristics in order to paint a comprehensive picture of the integration of the cryptocurrency market.

The main results provide evidence that Bitcoin and Litecoin are at the centre of the connected network of returns and that shocks arising from these two cryptocurrencies have the greatest effect on other cryptocurrencies. Connectedness via negative returns is stronger than via positive ones and that as far as the volatility spillovers are concerned, Bitcoin is the most influential cryptocurrency. Further analyses show that trading volumes, global financial and uncertainty effects, as well as the investment-substitution effect, are determinants of net directional spillovers.

The paper proceeds as follows: Section 2 reviews the related literature on the cryptocurrency market; Section 3 describes the econometric models; Section 4 presents the data and empirical results; Section 5 concludes.

2. Methodology

The methodological framework of this study for constructing connectedness measures follows the lines of Diebold and Yilmaz (2014). Specifically, positive/negative return and volatility connectedness networks are built. Furthermore, regression models are used to identify the drivers of the degree of integration of the various cryptocurrencies.

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[4] Corbet et al. (2018) focus on dynamic relationships between three cryptocurrencies and several financial assets.

Assume a stationary covariance six -variable VAR(p):

$$R_t = \sum_{i=1}^{p} \Phi_i R_{t-i} + \varepsilon_t , \qquad (1)$$

where R_t is the 6×1 vector of cryptocurrency returns, Φ_i are 6×6 autoregressive coefficient matrices and ε_t is the vector of error terms that are assumed to be serially uncorrelated. If the VAR system above is a stationary covariance, then a moving-average representation is written as $R_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, where the 6×6 coefficient matrix A_j obeys a recursion of the form $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \dots + \Phi_p A_{j-p}$, where A_0 is the $n\times n$ identity matrix and $A_j = 0$ for $j<0$. Using the moving-average framework, we can measure pairwise connectedness, directional connectedness and total connectedness based on the generalized forecast-error variance decomposition (FEVD) approach. The advantage of the FEVD method is that it can eliminate any disturbance induced on the results by the ordering of the variables.

Koop et al. (1996) and Pesaran and Shin (1998) proposed the following H -step-ahead generalized forecast-error variance decomposition:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i \right)}, \qquad (2)$$

where $\theta_{ij}(H)$ is the variance contribution of variable j to variable i, Σ is the variance matrix of the vector of errors ε and σ_{jj} is the standard deviation of the error term of the j^{th} equation. Finally, e_i is a selection vector with a value of 1 for the i^{th} element and 0 otherwise. The spillover index yields an $n\times n$ matrix $\theta(H) = \left[\theta_{ij}(H)\right]$, where each entry gives the contribution of variable j to the forecast-error variance of variable i. Own-variable and cross-variable contributions are contained in the main diagonal and off-diagonal elements, respectively, of the $\theta(H)$ matrix. Each entry in the $\theta(H)$ matrix is normalized by the row sum to ensure that the row sum is equal to 1. We then construct several measures to investigate the information spillover of the whole cryptocurrency-market system.

2.1 Connectedness measures

(1) Net pairwise connectedness

In general, $\theta_{ij} \neq \theta_{ji}$, according to the definition of FEVD. Consequently, the difference between θ_{ij} and θ_{ji} can be measured as the pairwise net connectedness. The net spillover effect from variable j to variable i can be measured by $\theta_{ij} - \theta_{ji}$. Subsequently, a directional connectedness network can be built based on pairwise net connectedness. In this network, each market is set as a node, and the condition in which a directional edge from i to j exists in the network is $\theta_{ji} - \theta_{ij} > 0$.

(2) Total directional connectedness "From" and "To"

We use total directional connectedness "From" and "To" to measure the total information spillover from and to each market. Total directional connectedness "From" is defined as the information inflow from other markets to one market, which is calculated as $C_{i \leftarrow \text{g}} = \sum_{j=1}^{N} \theta_{ij}, j \neq i$. Similarity, total directional connectedness "To" is defined as the information outflow from one market to other markets, which is calculated as $C_{\text{g} \leftarrow j} = \sum_{i=1}^{N} \theta_{ij}, i \neq j$.

(3) Total net connectedness

Total net connectedness measures the net information-spillover contribution of one node by the difference between total directional connectedness "To" and "From", defined as $C_i = C_{\text{g} \leftarrow i} - C_{i \leftarrow \text{g}}$.

(4) Total connectedness for the system

Finally, $TSI = \frac{1}{N} \sum_{i,j=1}^{N} \theta_{ij}, i \neq j$ is defined as the total spillover index to measure the integration or systemic risk of the cryptocurrency-market system.

2.2 Various connectedness network measures

In addition to returns connectedness, we investigate asymmetry in the connectedness of cryptocurrency markets. In the broad empirical findings, asset markets usually present asymmetry effects in response to good news and bad news (e.g., Apergis et al., 2017; Barunik et al., 2016). However, there is thus far no clear evidence in the cryptocurrency market to confirm this rule. In addition, cryptocurrency is a newly developed financial product, made possible by the improvement of blockchain technology. The future of the cryptocurrency market is uncertain due to its applications, policy regulations and whether traders in the cryptocurrency market are sensitive to volatility. Therefore, it is useful to analyse the asymmetric return spillovers among cryptocurrency markets in order to well understand the systemic risk of this system. For simplicity, we build positive- and negative-returns connectedness networks, respectively. The positive and negative returns series are measured as follows:

$$R(+) = \begin{cases} R_t, \text{ if } R_t > 0 \\ 0, \text{ otherwise} \end{cases} \tag{3}$$

$$R(-) = \begin{cases} R_t, \text{ if } R_t < 0 \\ 0, \text{ otherwise} \end{cases} \tag{4}$$

$$R_t = R(+) + R(-) \tag{5}$$

We also consider volatility connectedness. Referring to Diebold and Yilmaz (2016) and Garman and Klass (1980), we use daily range-based volatility to estimate volatility connectedness. The detailed estimation equation is as follows:

$$V = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2, \tag{6}$$

where h, l are the log daily high price and low price and o, c are the log opening price and close price, respectively.

2.3 Determinant modelling for total connectedness index

We build regression models to identify the determinants that can influence the integration degree of the cryptocurrency-market system. Referring to the existing literature, trading volume (Balcilar et al., 2017), global financial factors (Ji et al., 2018c; Bouri et al., 2017a, b & c), US uncertainties (Bouri et al., 2017a & b; Demir et al., 2018) and major commodity markets (Ji et al., 2018c; Bouri et al., 2017c; Bouri et al., 2018a) are chosen in the following regression[5]:

[5] Some previous literature had verified the validity of internet concern on influencing asset prices and their comovement (Guo and Ji, 2013; Ji and Guo, 2015a & b). Due to the limited search data of cryptocurrency during our sample period, we don't consider google trend as a determinant in this paper. But, the influence of internet concern on the integration of the cryptocurrency market should be an interesting research path in the future.

$$TSI_{t,l} = \alpha + \sum_{i=1}^{p} \beta_i Volume_i + \sum_{j=1}^{q} \beta_j FF_j + \sum_{h=1}^{m} \delta_h ISF_h + \sum_{k=1}^{n} \phi_k UF_k + \varepsilon_t \,, \qquad (7)$$

where $TSI_{t,l}$ denotes the dynamic total connectedness of the cryptocurrency-market system for returns, positive returns, negative returns and volatility. $Volume_i$ represents trading volume for each of the six cryptocurrencies in this paper. FF_j denotes global financial factors represented by the Global Financial Stress Index (GFSI) and MSCI World stock index. ISF_h indicates investment-substitution factors that measure the influence of capital inflow and outflow to major commodities. They are represented by the GSCI Energy index and Gold Bullion index. UF_k denotes the influence of uncertainty factors as represented by US economic policy uncertainty (EPU) and US VIX.

3. Empirical analysis

3.1 Data and sample analysis

Out of the 10 largest cryptocurrencies by market capitalization from https://coinmarketcap.com, we collected daily price data on six cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Dash) because the length of their price data is the longest. In fact, it covers almost two-and-a-half-year period. Accordingly, we had to excluded other leading cryptocurrencies such as Bitcoin cash, Cardano, Neo, and EOS, which have price data available for shorter period not exceeding the one year. In doing so, we ensured a relatively wider time span that allows us to make the most of our empirical analysis. Otherwise, if Bitcoin cash, Cardano, Neo, and EOS are kept, the common sample period would have been reduced significantly. In fact, our sample period spans from August 7, 2015 to February 22, 2018 (931 observations), as depicted by the availability of price data on some cryptocurrencies. Each of the six selected cryptocurrencies has a market value above 5 billion USD, and the combined market value of these six cryptocurrencies represents 72.06% of the total cryptocurrency market.[6] The empirical analyses are based on daily returns, calculated as the difference in the log of prices, and a daily range-based volatility, referring to Diebold and Yilmaz (2016).

[6] Bitcoin ranks first, accounting for 39.01% of the total cryptocurrency market, followed by Ethereum (18.99%), Ripple (8.73%), Litecoin (2.61%), Stellar (1.58%) and Dash (1.13%).

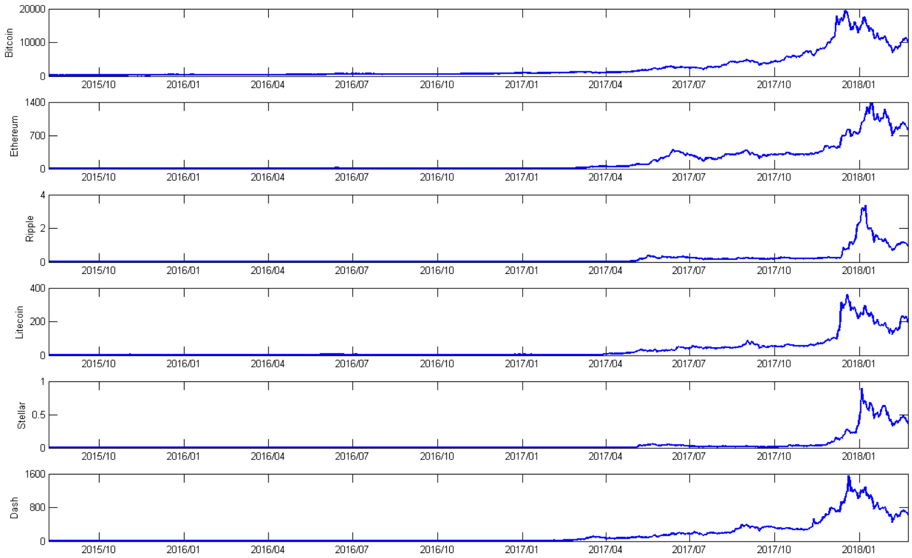

Figure 1. Historical trend of cryptocurrency prices

Figure 1 shows that the price trends of the six cryptocurrencies follow almost the same path, with substantial price appreciations experienced mostly during 2017. Notably, the prices of Bitcoin, Litecoin and Dash reached their peaks in late 2017, whereas Ethereum, Ripple and Stellar reached their highest prices during January 2018.

Table 1. Summary statistics for returns and volatility of cryptocurrencies

Panel A: Returns							
Variables	Mean	Max.	Min	Std. Dev	Skewness	Kurtosis	Jarque-Bera
Bitcoin	0.385	22.512	-20.753	4.114	-0.277	8.268	1087.184***
Ethereum	0.611	41.234	-130.211	8.485	-3.575	64.964	150762.400***
Ripple	0.511	102.736	-61.627	8.102	3.118	41.477	58875.780***
Litecoin	0.413	51.035	-39.515	6.022	1.453	16.493	7381.983***
Stellar	0.539	72.306	-36.636	9.075	2.081	17.345	8645.028***
Dash	0.567	43.775	-24.323	6.156	0.964	9.309	1686.675***
Panel B: Positive returns							
Bitcoin	1.510	22.512	0.000	2.599	3.047	16.268	8259.925***
Ethereum	2.825	41.234	0.000	5.144	2.845	13.780	5757.992***
Ripple	2.292	102.736	0.000	6.484	7.101	80.685	241673.500***
Litecoin	1.906	51.035	0.000	4.503	4.720	34.190	41148.470***
Stellar	2.990	72.306	0.000	6.923	5.043	38.535	52871.400***
Dash	2.335	43.775	0.000	4.399	3.534	21.361	14999.010***
Panel C: Negative returns							
Bitcoin	-1.126	0.000	-20.753	2.600	-3.581	18.643	11469.970***

Ethereum	-2.215	0.000	-130.211	5.745	-12.954	269.423	2776522.000***
Ripple	-1.781	0.000	-61.627	3.928	-6.432	73.235	197562.900***
Litecoin	-1.494	0.000	-39.515	3.207	-4.310	32.686	37027.750***
Stellar	-2.450	0.000	-36.636	4.446	-3.202	16.508	8660.302***
Dash	-1.769	0.000	-24.323	3.204	-3.030	14.831	6847.119***
Panel D: Volatility							
Bitcoin	0.288E-3	0.007	4.69E-07	6.89E-04	5.530	41.594	62457.59***
Ethereum	1.058 E-3	0.005	3.76E-06	2.56E-03	9.320	147.601	823709.9***
Ripple	0.918 E-3	0.006	1.01E-06	3.41E-03	9.028	111.929	472420.3***
Litecoin	0.556 E-3	0.025	5.61E-07	1.57E-03	7.927	93.087	324219.7***
Stellar	1.700 E-3	0.010	1.47E-05	5.14E-03	10.570	164.758	1031232***
Dash	1.121 E-3	0.241	1.46E-05	8.36E-03	26.101	736.627	20961190***

Note: *** denotes the significance at the 1% level.

The summary statistics of returns, including positive and negative returns as well as volatility, are given in Table 1. Results from Panel A indicate that the highest mean of returns is for Ethereum, followed by Dash. Stellar has the highest standard deviation, followed by Ethereum. Interestingly, Bitcoin has both the lowest mean returns and lowest standard deviation. This observation is not surprising, given the fact that, although Bitcoin increased by around 1300% in 2017, each of the other five cryptocurrencies under study increased in value by at least 5000%. All cryptocurrencies have excess levels of kurtosis, especially Ethereum. Bitcoin and Ethereum have a negative skewness, whereas the rest have a positive one. As for the summary statistics of positive returns (Panel B), Stellar has the highest average returns and standard deviation, whereas Bitcoin has the lowest ones. All series have excess kurtosis, especially Ripple, which also exhibits the highest skewness. Moving to the statistics of negative returns (Panel C), Stellar also has the highest negative returns, whereas Ethereum has the highest levels of standard deviation, kurtosis and negative skewness. In contrast, Bitcoin exhibits the lowest negative average returns and lowest standard deviation. Regarding the realized volatility of the six cryptocurrencies (Panel D), Stellar is the most volatile, while Bitcoin is the least; the volatility of volatility is highest for Dash, followed by Bitcoin, whereas Litecoin has the lowest volatility of volatility.

The correlation matrices among the returns and the volatility of the six cryptocurrencies are given in Table 2. Overall, weak to moderate positive correlations exist among the six cryptocurrencies' returns. Specifically, the correlation coefficients are highest for the pairs Bitcoin/Litecoin (0.551) and Ripple/Stellar (0.517), whereas Ethereum/Ripple and Ripple/Dash have the lowest correlation coefficients (0.133 and 0.147, respectively).

Expectedly, the correlation among negative returns is generally stronger than among positive returns. Considering negative returns, the Bitcoin/Litecoin pair has the highest correlation (0.760), followed by the pair Ripple/Stellar (0.618), whereas the lowest correlations are for the pairs Ethereum/Ripple (0.195) and Ethereum/Stellar (0.221).

As for the correlation between positive returns, Ripple and Stellar exhibit the highest positive correlation (0.453), followed by Bitcoin/Litecoin (0.367), while Ethereum and Ripple are uncorrelated. Moving to the correlation of price volatility, it is highest for the pair Bitcoin/Litecoin (0.706), while the weakest correlation is found between Dash and the other cryptocurrencies, which does not exceed the 0.098 mark in any instance. Overall, the correlation between the returns of Bitcoin and its fork Litecoin is unsurprisingly much stronger compared to the others, and that is also the case for positive/negative returns and for volatility.

Table 2. Correlations among cryptocurrency markets

Returns correlations

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash
Bitcoin	1					
Ethereum	0.288***	1				
Ripple	0.219***	0.133***	1			
Litecoin	0.551***	0.271***	0.279***	1		
Stellar	0.288***	0.177***	0.517***	0.319***	1	
Dash	0.375***	0.273***	0.147***	0.350***	0.209***	1

Positive returns correlations

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash
Bitcoin	1					
Ethereum	0.207***	1				
Ripple	0.116***	0.059	1			
Litecoin	0.367***	0.164***	0.247***	1		
Stellar	0.165***	0.088***	0.453***	0.211***	1	
Dash	0.261***	0.222***	0.084**	0.240***	0.111***	1

Negative returns correlations

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash
Bitcoin	1					
Ethereum	0.321***	1				
Ripple	0.381***	0.195***	1			
Litecoin	0.760***	0.323***	0.412***	1		
Stellar	0.429***	0.221***	0.618***	0.472***	1	
Dash	0.547***	0.287***	0.391***	0.537***	0.398***	1

Volatility correlations

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash
Bitcoin	1					
Ethereum	0.302***	1				
Ripple	0.397***	0.202***	1			
Litecoin	0.706***	0.283***	0.567***	1		
Stellar	0.323***	0.158***	0.478***	0.427***	1	
Dash	0.093***	0.049	0.085***	0.098***	0.047	1

Note: *** denotes the significance at the 1% level.

3.2 Static connectedness-network analysis

3.2.1 Returns connectedness network over the full sample

Table 3 presents the matrix of directional spillovers among cryptocurrencies, directional spillovers from each cryptocurrency to all other cryptocurrencies ("To others") and directional spillovers from all other cryptocurrencies to each cryptocurrency ("From others"). Table 3 also reports the net directional spillover ("Net"), where a positive (negative) value indicates that the corresponding cryptocurrency is a net transmitter (receiver) of spillover effects.

Table 3. Full-sample connectedness matrix for cryptocurrency returns

Returns	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From others
Bitcoin	0.592	0.058	0.032	0.183	0.050	0.086	0.408
Ethereum	0.072	0.744	0.020	0.061	0.033	0.071	0.256
Ripple	0.037	0.019	0.683	0.061	0.184	0.016	0.317
Litecoin	0.180	0.048	0.049	0.583	0.064	0.075	0.417
Stellar	0.054	0.028	0.172	0.071	0.649	0.026	0.351
Dash	0.101	0.063	0.021	0.090	0.029	0.697	0.303
To others	0.443	0.215	0.294	0.466	0.360	0.275	**TSI=0.342**
Net	**0.035**	**-0.041**	**-0.023**	**0.049**	**0.008**	**-0.028**	

Notes: This table presents the net directional spillover amongst the returns of the six cryptocurrencies over the period August 7, 2015–February 22, 2018. Net: spillover transmitted by each cryptocurrency to all other cryptocurrencies, where positive (negative) values indicate that the currency in question is a net transmitter (receiver) of spillovers to all other cryptocurrencies. TSI: total spillover index.

Litecoin is the largest net transmitter of spillover, followed by Bitcoin; interestingly, these two cryptocurrencies are also the two largest transmitters and receivers of spillover effects from other cryptocurrencies. The two largest net receivers of spillovers are Ethereum and Dash; again, these two cryptocurrencies are the smallest transmitters and receivers of spillover effects from other cryptocurrencies. The spillover index (TSI) reaches 34.20%, indicating a sizable degree of connectedness among the six cryptocurrencies during the sample period, which exhibits substantial increases in the prices of all cryptocurrencies. This result indicates that these cryptocurrencies are linked with each other, adding to the results from the correlation matrix in Table 2.

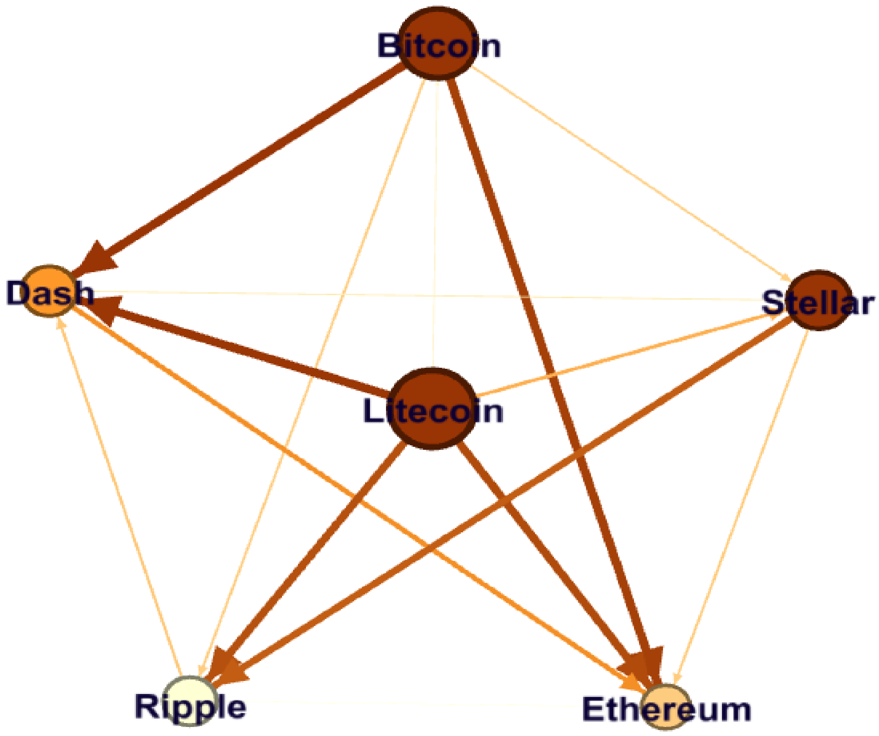

Figure 2. Directional-returns connectedness network over the full sample
Notes: This figure shows the net directional connectedness among the six cryptocurrencies' returns. The size of each node indicates the overall magnitude of spillover transmission for each cryptocurrency, which is measured by net connectedness in Table 3. The thickness of the arrows reflects the strength of the spillover between a pair of variables, with thicker arrows indicating stronger net directional pairwise connectedness.

To better visualize the structure of connectedness, the direction and the strength of spillovers between the six cryptocurrencies, Figure 2 provides the network of pairwise return connectedness.[7] Litecoin and Bitcoin are at the centre of the connected network. They are both strongly connected with Ethereum and Dash, while Litecoin is more connected with Ripple than is Bitcoin.

However, Litecoin and Bitcoin are the least connected to each other, with the former surprisingly transmitting its return spillovers to the largest cryptocurrency, Bitcoin. Interestingly, the importance of Stellar in the network is also clear, especially through its strong connection with Ripple. Litecoin is the largest transmitter, followed by Bitcoin; whereas Ethereum is the largest receiver, followed by Dash and Ripple. It is worthy of note that no direct connection exists between Ethereum and Ripple, suggesting potential diversification benefits.

[7] The size of the node captures the importance of each cryptocurrency within the network structure, whereas the thickness of the arrows indicates the magnitude of the spillover for each cryptocurrency. As for the node colours, dark (light) colours indicate a large (small) influence on network connectedness.

3.2.2 Asymmetric-connectedness analysis over the full sample

The previous analysis considered the return connectedness among cryptocurrencies. However, it is possible that positive returns and negative returns are perceived differently by market participants and that connectedness may exhibit asymmetries. To address this potential asymmetry, we decompose returns into positive and negative returns and present the resulting connectedness matrix in Table 4.

Table 4. Full-sample connectedness matrix for positive returns and negative returns of cryptocurrencies

Positive Returns							
	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From others
Bitcoin	0.773	0.037	0.009	0.102	0.022	0.056	0.227
Ethereum	0.041	0.875	0.003	0.025	0.009	0.047	0.125
Ripple	0.009	0.004	0.736	0.071	0.169	0.010	0.264
Litecoin	0.105	0.020	0.043	0.752	0.035	0.045	0.248
Stellar	0.017	0.008	0.140	0.036	0.789	0.009	0.211
Dash	0.060	0.045	0.005	0.051	0.011	0.827	0.173
To others	0.233	0.114	0.199	0.286	0.246	0.167	**TSI=0.208**
Net	**0.007**	**-0.011**	**-0.064**	**0.038**	**0.035**	**-0.005**	
Negative Returns							
	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From others
Bitcoin	0.424	0.064	0.064	0.244	0.078	0.126	0.576
Ethereum	0.094	0.601	0.053	0.093	0.068	0.091	0.399
Ripple	0.076	0.046	0.510	0.087	0.191	0.090	0.490
Litecoin	0.240	0.064	0.072	0.412	0.092	0.120	0.588
Stellar	0.090	0.056	0.182	0.110	0.483	0.079	0.517
Dash	0.148	0.071	0.074	0.142	0.077	0.488	0.512
To others	0.649	0.300	0.444	0.676	0.507	0.506	**TSI=0.514**
Net	**0.073**	**-0.099**	**-0.046**	**0.088**	**-0.010**	**-0.006**	

Note: See notes to Table 3.

Litecoin and Stellar are the two largest net transmitters of positive-return spillovers, whereas Ripple is the largest net receiver of positive-return spillovers. The two largest net transmitters of negative-return spillovers are Litecoin and Bitcoin, whereas Ethereum and Ripple are the two largest net receivers of negative-return spillovers. Importantly, the TSI of negative returns is almost 2.5 times stronger than that of positive returns, highlighting an intensified connectedness during the downturn state of cryptocurrencies.

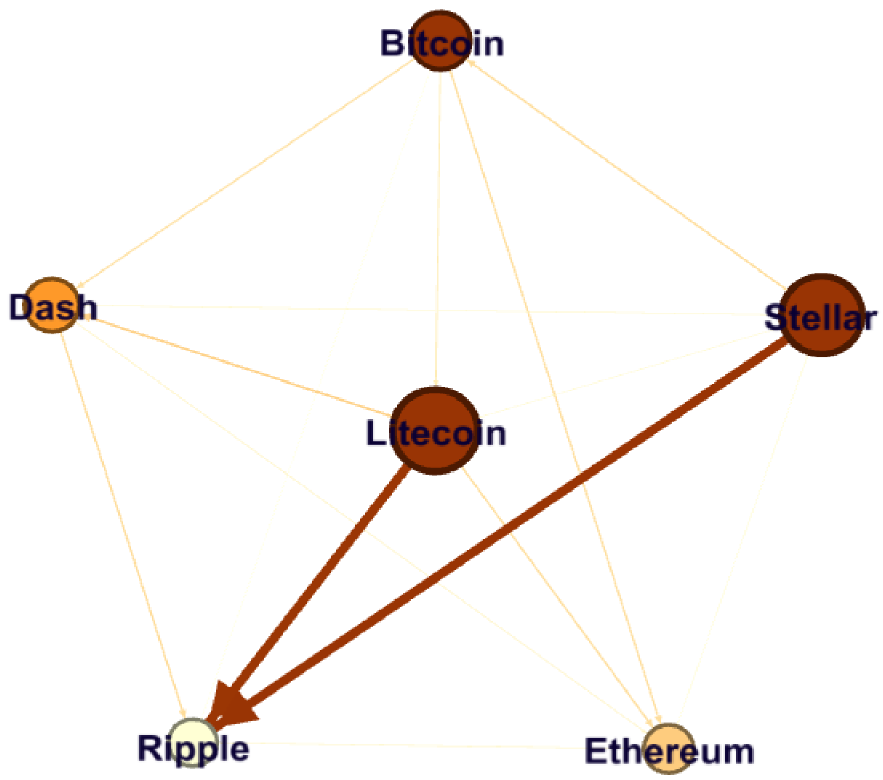

Figure 3. Directional positive-returns connectedness network over the full sample

Note: See Figure 2.

Moving to the structure of connectedness between positive returns (Figure 3), it appears that a weaker connectedness network emerges between positive returns. Litecoin is firmly at the centre of the network, and Stellar surprisingly exhibits a more important spillover role than Bitcoin. Specifically, Litecoin and Stellar are the two largest transmitters of spillovers, whereas Ripple is the largest receiver. Interestingly, Ethereum is the least connected to the other cryptocurrencies, especially with the lack of direct connectedness between Ethereum and Ripple and Ethereum and Stellar, which suggests diversification and hedging possibilities.

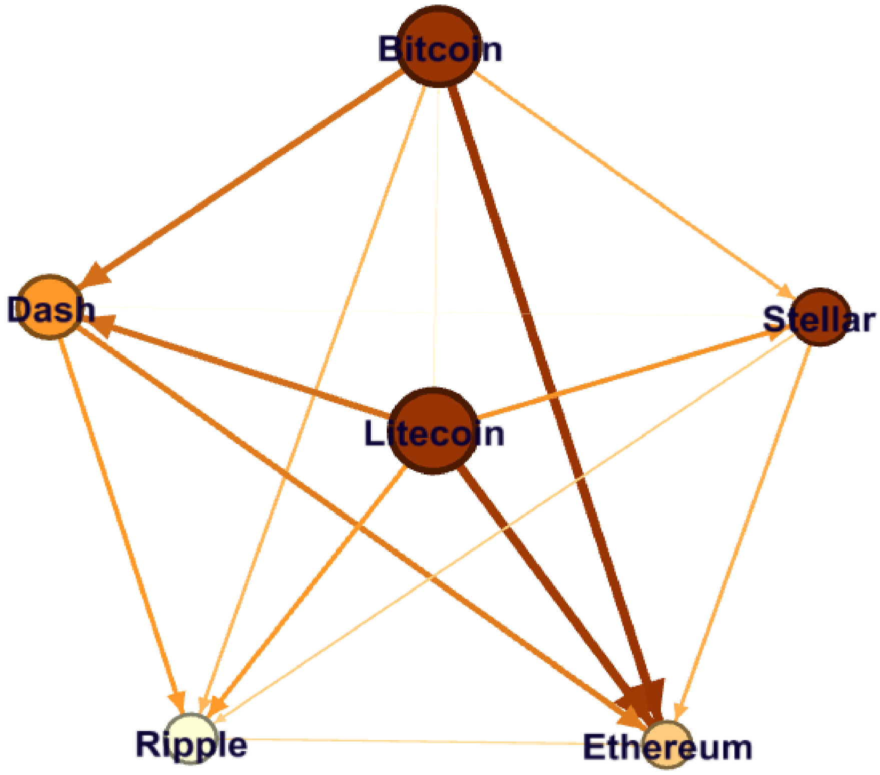

Figure 4. Directional negative-returns connectedness network over the full sample

Note: See Figure 2.

The network diagram of pairwise connectedness using negative returns of cryptocurrencies is shown in Figure 4. Litecoin and Bitcoin are the greatest transmitters of negative shocks, whereas Ethereum and Ripple are the greatest receivers of negative shocks. The pair Bitcoin/Ethereum has the strongest connectedness, followed by Litecoin/Ethereum. The lowest connectedness is reported for the pairs Bitcoin/Litecoin and Ripple/Ethereum. Although Ethereum is second in market value, it has almost no influence on other, smaller cryptocurrencies (Litecoin, Ripple, Stellar and Dash). In contrast, smaller cryptocurrencies (Stellar and Dash) are found to transmit negative shocks to larger cryptocurrencies (Ethereum and Ripple).

To summarize, the overall connectedness, including the strength of spillovers, among negative returns is stronger than across positive ones, suggesting that return spillovers due to negative shocks materialize more frequently. Therefore, in terms of return spillovers, cryptocurrency investors are not attuned to positive signals only.

3.2.3 Volatility-connectedness network analysis over the full sample

The connectedness matrix of volatility spillover is reported in Table 5. Contrary to its position in the case of return spillovers, Bitcoin is the largest net transmitter of volatility spillover, followed by Litecoin. Interestingly, these two cryptocurrencies are both also the largest transmitters and receivers of spillover effects from the other cryptocurrencies. The two largest net receivers of spillovers are Ethereum and Stellar; again, these two cryptocurrencies are the smallest transmitters and receivers of spillover effects. The total volatility spillover across the six cryptocurrencies is 32.90%. That is quite similar to that of returns in Table 3. Intuitively, the spillover index indicates a sizable degree of connectedness among the six cryptocurrencies in the period under study, during which all of them experienced substantial price volatility.

Table 5. Full-sample connectedness matrix for range-based volatility of cryptocurrencies

Volatility	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From others
Bitcoin	0.564	0.056	0.086	0.241	0.050	0.004	0.436
Ethereum	0.083	0.776	0.043	0.074	0.022	0.002	0.224
Ripple	0.100	0.031	0.585	0.158	0.124	0.003	0.415
Litecoin	0.251	0.044	0.157	0.467	0.077	0.003	0.533
Stellar	0.072	0.021	0.137	0.106	0.662	0.001	0.338
Dash	0.009	0.003	0.007	0.009	0.002	0.971	0.029
To others	0.515	0.154	0.431	0.588	0.275	0.013	**TSI=0.329**
Net	**0.078**	**-0.070**	**0.016**	**0.056**	**-0.063**	**-0.016**	

Note: See notes to Table 3.

Interestingly, Dash (Litecoin) depends more (less) on its own volatility than the others, suggesting a weak (strong) volatility connectedness with the other cryptocurrencies under study; this finding points to the ability of Dash to reduce the overall risk of a portfolio of leading cryptocurrencies. Specifically, Litecoin appears to have a strong influence on the other cryptocurrencies, which cannot be explained by its relatively small size[8] but can be better explained by the fact that Litecoin is a fork of the largest and most popular cryptocurrency, Bitcoin.

[8] Among the six cryptocurrencies under study, Litecoin's market value is ranked fourth.

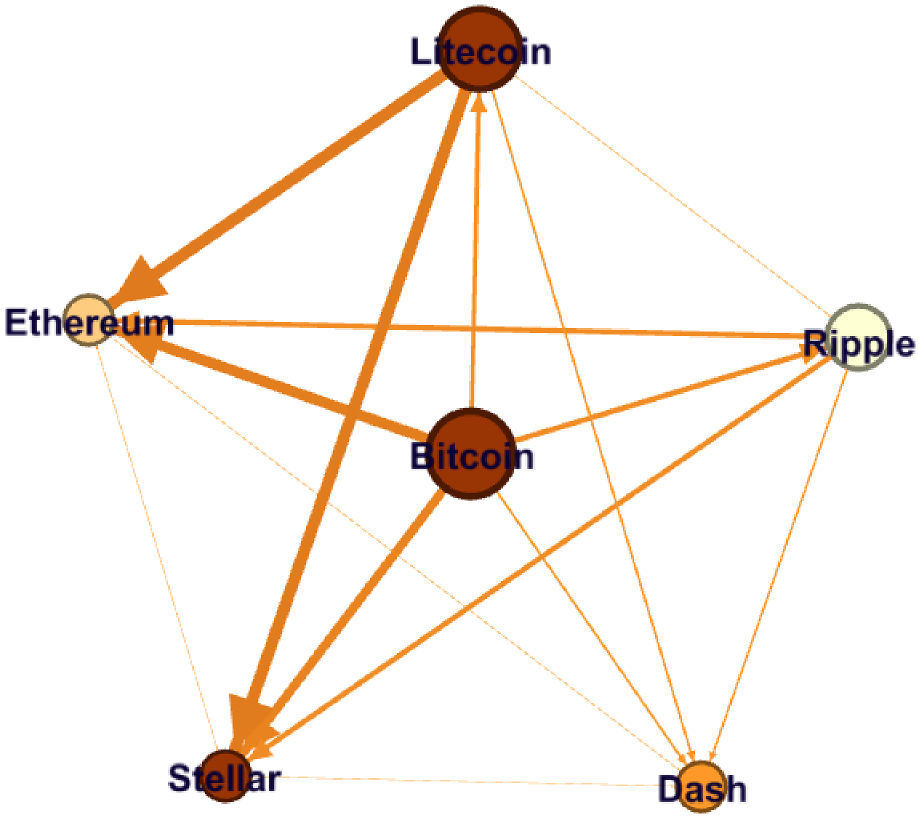

Figure 5. Directional-volatility connectedness network over the full sample

Note: See Figure 2.

The structure of volatility connectedness is shown in Figure 5. Interestingly, Bitcoin is at the centre of volatility connectedness, as it is the most influential cryptocurrency and transmits volatility spillovers to each of the five cryptocurrencies, including Litecoin. Also important is the role of Litecoin as a large volatility transmitter, especially to Ethereum and Stellar. All of the six cryptocurrencies are interconnected, with substantial differences in the degree and magnitude of the volatility spillovers. Stellar is the largest receiver of volatility spillovers, followed by Ethereum. Dash is the least influential in the network of connectedness, offering potential diversification benefits if combined in a portfolio with each of the other cryptocurrencies. On a one-to-one basis, there is noticeably a very weak connectedness across the pairs Ethereum/Stellar, Ethereum/Dash and Litecoin/Ripple.

3.2.4 Robustness test based on subsample data

Our full sample period includes the 2017 bull market for cryptocurrencies, which may have an increasing effect on the connectedness because of the strong market interest towards all the cryptocurrencies. To test the robustness of our full-sample results, two different subsample periods are considered for further investigation: Subsample I (07/08/2015-31/12/2016) which and subsample II (01/01/2017-22/02/2018). The first includes a “stable” market where cryptocurrencies tended to move horizontally, while the second includes the 2017 bull market. The connectedness matrices for original returns, positive returns, negative returns, and volatility for the two subsamples are presented in Table 6-7. “The results show that there are some similarity and difference in our subsamples compared with the full-sample results. First, Bitcoin and Litecoin are the largest transmitters in the returns and volatility cryptocurrency connectedness system, while Ripple and Ethereum always tend to be the top recipients in response to shocks from other cryptocurrencies in most of the two subsamples. This finding is consistent with our full-sample results, which show the stability of interdependence among cryptocurrencies. Another similar finding is that connectedness via negative returns is also largely stronger than via positive ones in the two subsamples. For example, in subsample II, the TSI in the positive return connectedness network is only 0.228, while the TSI in the negative one reaches 0.618. The largest difference between the two subsamples is the connectedness intensity in the cryptocurrency system. In the subsample I, the TSI in the return and volatility connectedness networks are around 0.2, while in subsample II, the TSI in the return and volatility connectedness networks are relatively higher, reaching above 0.4. It indicates that the connectedness tightness among cryptocurrencies has largely strengthened since 2017 when the cryptocurrency market entered into a bull market. Sharp price rise and active market trading have increased the comovement of cryptocurrency returns.

Table 6. Connectedness matrix for cryptocurrencies based on subsample I (07/08/2015-31/12/2016)

Returns

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.578	0.007	0.021	0.336	0.025	0.033	0.422
Ethereum	0.012	0.964	0.003	0.009	0.003	0.009	0.036
Ripple	0.030	0.004	0.831	0.022	0.101	0.012	0.169
Litecoin	0.346	0.002	0.016	0.596	0.017	0.022	0.404
Stellar	0.035	0.003	0.095	0.028	0.829	0.010	0.171
Dash	0.045	0.008	0.013	0.031	0.010	0.893	0.107
To	0.469	0.024	0.148	0.427	0.155	0.086	**TSI=0.218**
Net	**0.047**	**-0.012**	**-0.021**	**0.023**	**-0.016**	**-0.021**	

Positive returns

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.691	0.008	0.004	0.275	0.006	0.018	0.309
Ethereum	0.012	0.967	0.000	0.005	0.001	0.015	0.033
Ripple	0.008	0.001	0.880	0.004	0.103	0.005	0.120
Litecoin	0.280	0.004	0.004	0.697	0.001	0.013	0.303
Stellar	0.007	0.003	0.087	0.001	0.893	0.008	0.107
Dash	0.026	0.019	0.007	0.017	0.009	0.922	0.078
To	0.333	0.035	0.103	0.303	0.119	0.059	**TSI=0.159**
Net	**0.024**	**0.001**	**-0.018**	**0.000**	**0.011**	**-0.019**	

Negative returns

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.518	0.008	0.043	0.350	0.043	0.037	0.482
Ethereum	0.016	0.937	0.009	0.007	0.016	0.016	0.063
Ripple	0.062	0.011	0.813	0.043	0.059	0.013	0.187
Litecoin	0.362	0.004	0.036	0.536	0.033	0.029	0.464
Stellar	0.067	0.011	0.060	0.051	0.809	0.003	0.191
Dash	0.062	0.013	0.014	0.047	0.003	0.862	0.138
To	0.569	0.047	0.163	0.498	0.154	0.096	**TSI=0.254**
Net	**0.087**	**-0.016**	**-0.024**	**0.034**	**-0.038**	**-0.042**	

Volatility

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.557	0.017	0.033	0.390	0.003	0.000	0.443
Ethereum	0.029	0.934	0.002	0.033	0.003	0.000	0.066
Ripple	0.065	0.002	0.862	0.044	0.027	0.000	0.138
Litecoin	0.396	0.015	0.021	0.567	0.000	0.000	0.433
Stellar	0.002	0.005	0.026	0.014	0.953	0.001	0.047
Dash	0.000	0.000	0.000	0.000	0.000	0.999	0.001
To	0.493	0.039	0.082	0.480	0.035	0.001	**TSI=0.188**
Net	**0.050**	**-0.028**	**-0.056**	**0.047**	**-0.013**	**0.000**	

Note: See notes to Table 3.

Table 7. Connectedness matrix for cryptocurrencies based on subsample II (01/01/2017-22/02/2018)

Returns

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.542	0.125	0.033	0.139	0.053	0.107	0.458
Ethereum	0.123	0.543	0.031	0.108	0.059	0.135	0.457
Ripple	0.038	0.036	0.641	0.066	0.203	0.015	0.359
Litecoin	0.138	0.106	0.051	0.537	0.076	0.092	0.463
Stellar	0.056	0.062	0.182	0.081	0.586	0.033	0.414
Dash	0.117	0.136	0.021	0.100	0.036	0.590	0.410
To	0.472	0.465	0.319	0.494	0.427	0.383	**TSI=0.427**
Net	**0.014**	**0.008**	**-0.040**	**0.032**	**0.013**	**-0.027**	

Positive returns

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.781	0.079	0.005	0.058	0.014	0.061	0.219
Ethereum	0.075	0.765	0.006	0.045	0.020	0.088	0.235
Ripple	0.005	0.009	0.736	0.068	0.177	0.005	0.264
Litecoin	0.059	0.041	0.042	0.773	0.041	0.045	0.227
Stellar	0.010	0.017	0.147	0.039	0.782	0.006	0.218
Dash	0.067	0.081	0.005	0.046	0.009	0.793	0.207
To	0.216	0.227	0.205	0.256	0.261	0.204	**TSI=0.228**
Net	**-0.003**	**-0.008**	**-0.059**	**0.029**	**0.043**	**-0.003**	

Negative returns

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.364	0.155	0.059	0.194	0.077	0.152	0.636
Ethereum	0.157	0.356	0.081	0.159	0.107	0.141	0.644
Ripple	0.072	0.100	0.440	0.082	0.203	0.103	0.560
Litecoin	0.190	0.156	0.065	0.352	0.095	0.142	0.648
Stellar	0.086	0.121	0.185	0.108	0.401	0.100	0.599
Dash	0.160	0.144	0.076	0.151	0.092	0.378	0.622
To	0.664	0.675	0.466	0.693	0.574	0.638	**TSI=0.618**
Net	**0.028**	**0.031**	**-0.094**	**0.045**	**-0.026**	**0.016**	

Volatility

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Dash	From
Bitcoin	0.425	0.160	0.066	0.175	0.038	0.136	0.575
Ethereum	0.159	0.401	0.102	0.150	0.046	0.142	0.599
Ripple	0.080	0.116	0.484	0.122	0.094	0.104	0.516
Litecoin	0.189	0.142	0.115	0.370	0.056	0.127	0.630
Stellar	0.064	0.076	0.112	0.088	0.608	0.052	0.392
Dash	0.148	0.154	0.118	0.138	0.037	0.406	0.594
To	0.641	0.647	0.514	0.672	0.270	0.561	**TSI=0.551**
Net	**0.066**	**0.048**	**-0.002**	**0.043**	**-0.121**	**-0.033**	

Note: See notes to Table 3.

3.3 Dynamic-connectedness network analysis

3.3.1 Dynamic-return connectedness network

The results presented in Table 3 summarize the net connectedness of cryptocurrencies, yet they overlook any time variation in the spillover effect. Therefore, we report in Figure 6 the time evolution of the total connectedness for cryptocurrency returns.

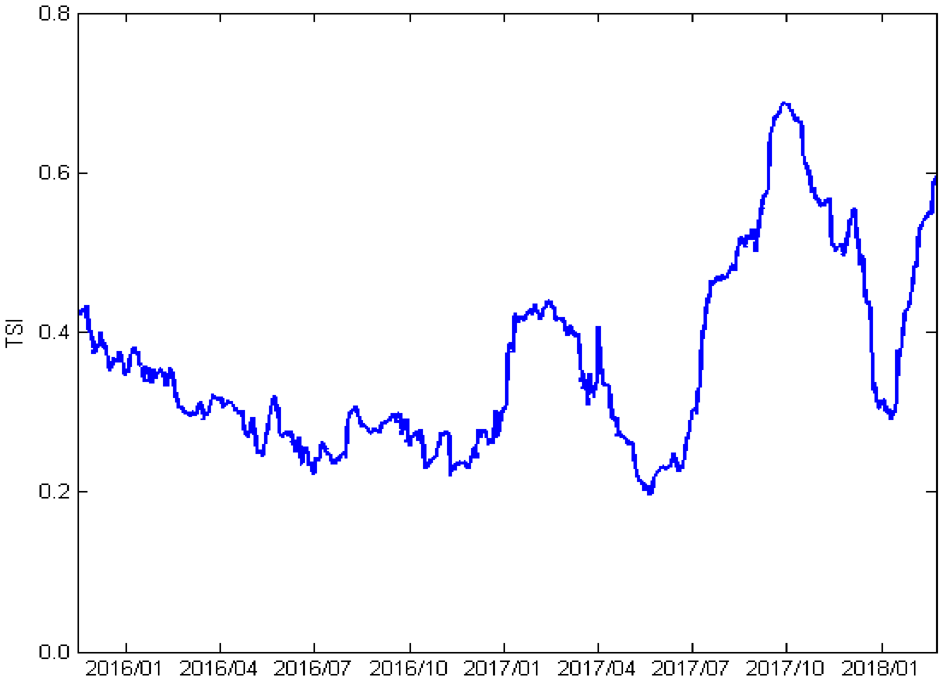

Figure 6. Dynamic total connectedness for cryptocurrency returns

The TSI varies substantially over time. In particular, it declines during 2016 from over 40% to around 20% and then oscillates between 40% and 20% before peaking at around 70% in October 2017. After that, it retraces most of the upward movement before experiencing a sharp upward movement to around 60% at the end of the period under study. The time-varying nature of the TSI confirms the spike in the levels of spillover during 2016 and 2017, possibly due to the hack of the Bitfinex exchange, which created uncertainty to the cryptocurrency market. The introduction of Ripple, acting as bridge currency for real-time settlement and allowing for the efficient exchange of value across borders (Corbet et al., 2018), and the subsequent introduction of the Ripple/Bitcoin trading pair may increase the connectedness of the cryptocurrency market.

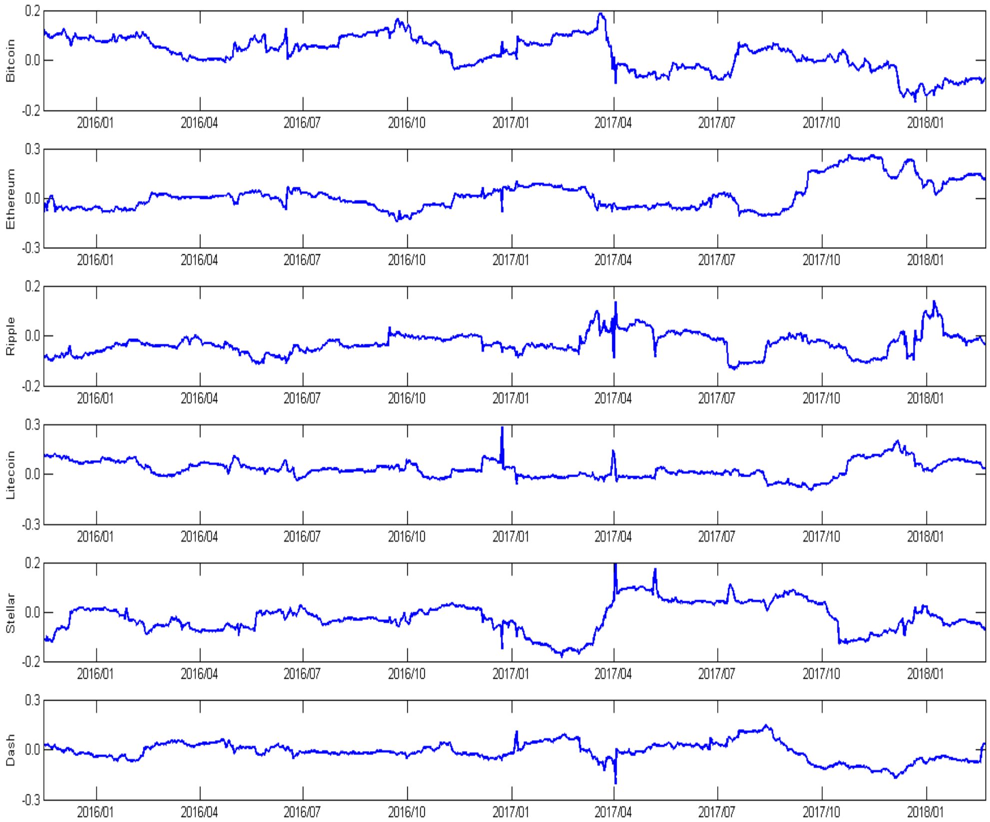

Figure 7. Dynamic total net connectedness for cryptocurrency returns

The time-varying of net directional return spillovers from each cryptocurrency to all other cryptocurrencies is shown in Figure 7. In most of the cases, the net spillover effects switch between negative and positive territories, suggesting that each cryptocurrency can act as a net transmitter or a net receiver at given points of time.[9] Specifically, Bitcoin is a net transmitter from the beginning of the sample period until April 2017, whereas it behaves more as a net receiver afterwards, especially toward the end of the period. Ethereum oscillates between positive and negative territories until the end of the period, when it acts as a net transmitter. Litecoin is more a net transmitter, especially toward the end of the sample period. Stellar, Ripple and Dash exhibit no particular pattern, although the latter clearly acts as a net receiver.

[9] Positive (negative) values indicate that the cryptocurrency is a net transmitter (receiver) of spillover effects.

3.3.2 Dynamic-asymmetric connectedness analysis

The above analyses do not consider potential asymmetries in the return spillovers but merely provide evidence that the net directional return spillovers from each cryptocurrency to all other cryptocurrencies vary over time. Accordingly, we differentiate between positive and negative returns in order to uncover the asymmetries in return connectedness within the framework of Diebold and Yilmaz (2016). The results of the dynamics of connectedness for positive returns and negative returns are reported in Figures 8 and Figure 9, respectively. It appears from Figure 8 that Bitcoin and Litecoin may be aptly described as positive-return transmitters. As for the dynamics of connectedness for negative returns (Figure 9), the picture is different from the one associated with positive returns in Figure 8.

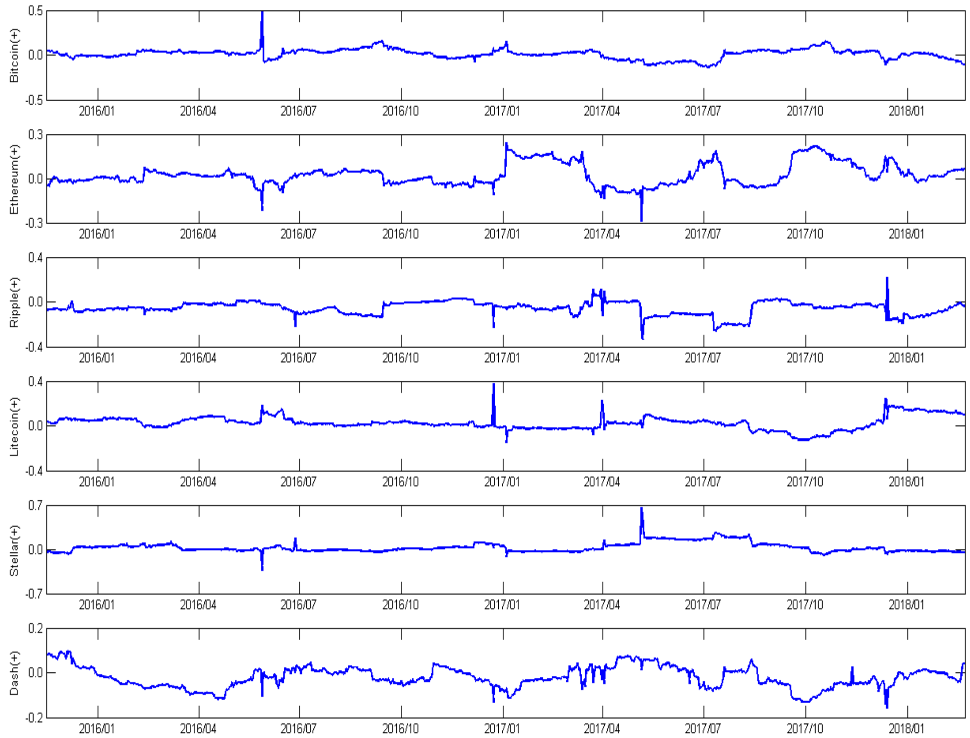

Figure 8. Dynamic total net connectedness for cryptocurrency positive returns

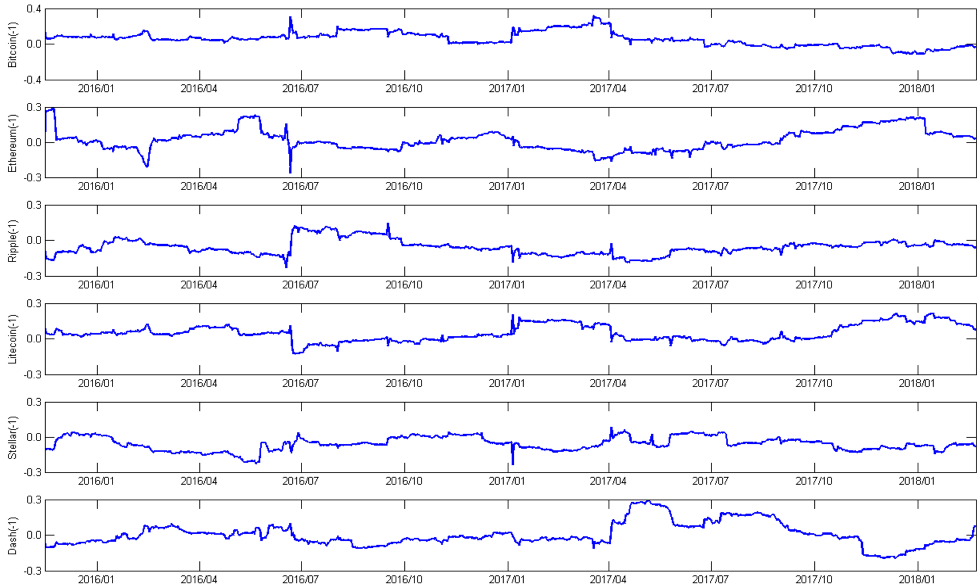

Figure 9. Dynamic total net connectedness for cryptocurrency negative returns

To provide evidence for the intuition that returns movement among cryptocurrency markets is asymmetrical in response to positive and negative information shocks, the dynamic total connectedness and asymmetry indicators for cryptocurrency positive and negative returns are presented in Figure 10. The asymmetry indicator is measured by TSI(-)/TSI(+). A TSI(-)/TSI(+) of larger than 1 indicates that bad news contributes more to system risk than good news. Figure 10 clearly shows the overall presence of an asymmetric effect.

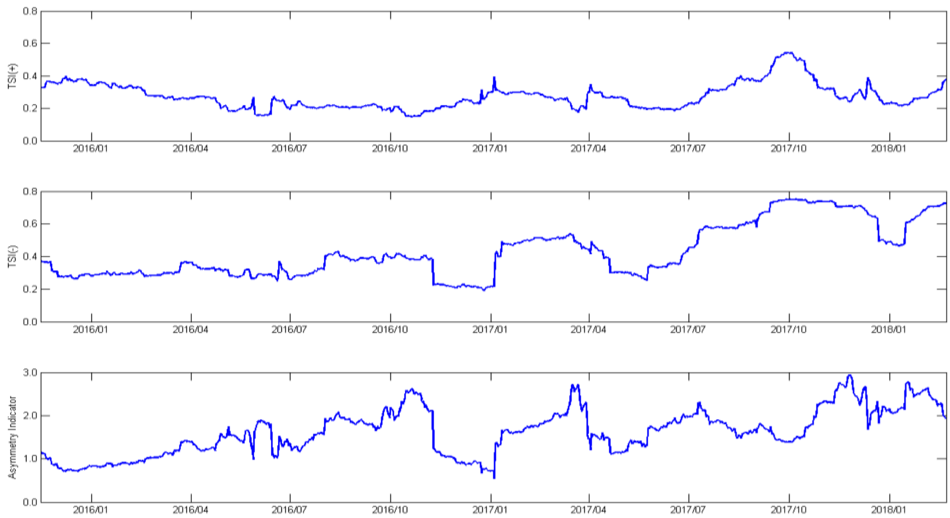

Figure 10. Dynamic total connectedness and asymmetry indicators for cryptocurrency positive and negative returns

3.3.3 Dynamic-volatility connectedness network analysis

The TSI of cryptocurrency volatilities (Figure 11) fluctuates sharply between 10% and over 80%, confirming a considerable time-varying feature. Specifically, the peaks correspond to the introduction of Ripple on major exchanges, such as Bitstamp, and to new trading-pair arrangements in 2017, whereas most of the troughs coincide with increasing uncertainty on economic policy and blockchain security. These periods coincide with several structural events.[10]

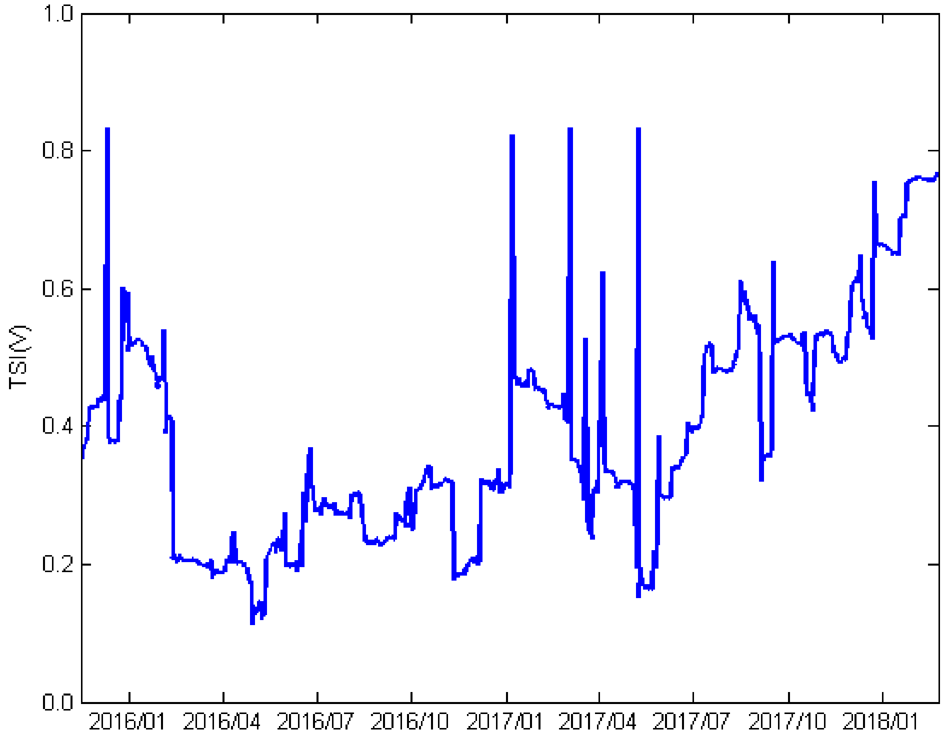

Figure 11. Dynamic total connectedness for cryptocurrency volatilities

Moving to the time-varying of net directional-volatility spillovers from each cryptocurrency to all other cryptocurrencies, Figure 12 shows evidence of large fluctuations in the cases of Litecoin and, to a lesser extent, Bitcoin, especially around the beginning and middle of the sample period. In contrast, Ripple, Stellar and Ethereum appear to be the calmest cryptocurrencies, as the net directional-volatility spillovers are quite low.

[10] For example, Bitstamp brought in the first Ripple/Bitcoin trading pair on 16 February 2017, providing digital assets and a bridge currency to the market for real-time settlement. This allows for the efficient exchange of value across borders.

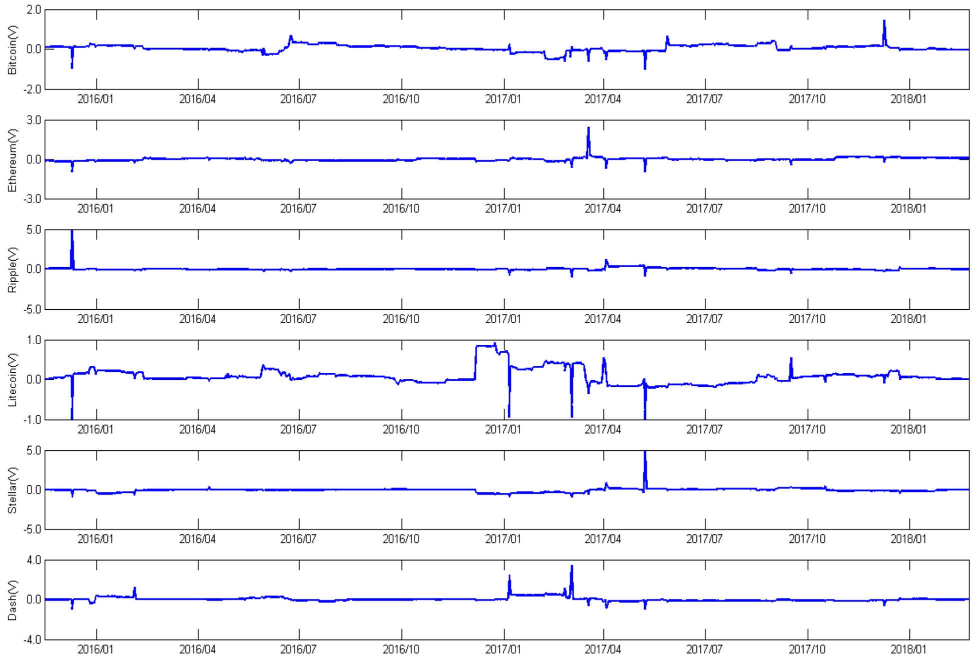

Figure 12. Dynamic net connectedness for cryptocurrency volatilities

3.4 Determinants of cryptocurrency integration

We consider the determinants of the cryptocurrency market's returns and volatility connectedness by considering a set of financial, economic and other variables.[11] As indicated in the methods section, our choice for these explanatory variables depends on prior studies.

Results from the OLS regressions are reported in Tables 8–11.[12] Tables 8-10 reports the regression coefficients for returns, positive returns, and negative returns respectively, while table 11 reports the results for volatility. The results reveal that the coefficient of trading volume of most of the cryptocurrencies is significant in many cases, but its sign is mixed. Specifically, it is positive for Bitcoin, Litecoin and Stellar and negative for the others. However, the trading volume for Litecoin exhibits a negatively significant impact on the net pairwise directional negative-return spillovers, whereas Stellar exhibits a negatively significant impact on the net pairwise directional positive-return spillovers.

[11] Table A in the Appendix describes the set of these explanatory variables.

[12] The adjusted R-squared for the regression models varies between 35.40% and 52.50% (see the last row in Tables 8-11).

For the empirical findings of “Total Connectedness”, “Positive Returns Connectedness”, and “Negative returns Connectedness”, the results among the four specifications are consistent in the sense that new additional variables/controls do not affect the role played by the volumes of the cryptocurrencies[13]. Although the direct linkage between trading volume and “return connectedness” for the cryptocurrency markets remains unexplored, one may expect a significant linkage between “return connectedness” and “trading volumes” given that there is a strong relationship between “return” and “trading volumes”. Our finding is therefore in line with Balcilar et al. (2017) and Bouri et al. (2018c) who find evidence of Granger causality from trading volume to the returns in the cryptocurrency market.

Interestingly we observed that for some cryptocurrencies (depends on the statistical significance level), the volumes are not significantly affecting volatility[14]. There is also variation in statistical significance regarding to whether some additional variables are included in the model specification. This finding may be justified by the fact that omitted variables may be an issue if we ignored some important regressors in the specification[15]. The last model consists of all important variables including magnitude effect, global financial effect, investment substitution effect, and uncertainty effect. There are only three cryptocurrencies with magnitude coefficient of 5 percent significant level, namely Bitcoin, Ripple, and Dash. We found significant positive coefficient of trading activity for the connectedness of volatility in Bitcoin market. The result is not surprising as Bitcoin has the highest market capitalization accounted for 39% of the cryptocurrency market at the end of 2017, and it is the dominant contributor of volatility spillovers in the cryptocurrency market and it has enjoyed more influence over other cryptocurrencies (Koutmos, 2018). The negative coefficient attached to Ripple and Dash may be attributed to the fact that they are the net volatility recipient, and therefore they have less influence over other cryptocurrencies. Furthermore, transaction cost of cryptocurrencies may play a role on volatility connectedness as the transaction cost of Bitcoin is lower than that of retail foreign exchange markets, and this may encourage algorithmic trading and thus become a dominant force on Bitcoin trading volume (and hence

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[13] We would like to thank the anonymous reviewer for raining this interesting

[14] For example, volumes of Ethereum and Litecoin are not significant at 5 percent significant level for all model specifications.

[15] The adjusted R^2 is the highest among all 4 model specifications.

increase cryptocurrency market's stability). As reported by Garcia and Schweitzer (2015), very high profits are earned in less than a year by using algorithmic trading strategy that takes into account of social media sentiment. It is also interesting to note that Yang (2018) found evidence that speculators plays extreme weight in the Bitcoin market, while Yeh and Yang (2011) emphasized the role of speculator's overconfidence that can increase market volatility. Also new information can cause price volatility to rise due to differences in its interpretation among traders in different market (Gębka, 2012).

Table 8. Determinants of dynamic total connectedness for returns

Coefficient		Model 1	Model 2	Model 3	Model 4
Constant		-0.733***	-13.671***	-17.173***	-16.904***
		(0.088)	(1.450)	(1.402)	(1.432)
Magnitude effect	Volume (Bitcoin)	0.087***	0.031***	0.029***	0.025***
		(0.008)	(0.010)	(0.009)	(0.008)
	Volume (Ethereum)	-0.015***	-0.030***	-0.023***	-0.028***
		(0.005)	(0.004)	(0.004)	(0.004)
	Volume (Ripple)	-0.023***	-0.020***	-0.013***	---
		(0.004)	(0.003)	(0.005)	
	Volume (Litecoin)	---	0.016***	---	---
			(2.940)		
	Volume (Stellar)	0.010**	---	---	0.010**
		(0.005)			(0.005)
	Volume (Dash)	-0.009**	---	-0.014***	-0.012***
		(0.004)		(0.004)	(0.004)
Global financial effect	GFSI		0.048***	0.071***	0.052***
			(0.008)	(0.008)	(0.010)
	MSCI World		1.877***	3.132***	3.092***
			(0.208)	(0.234)	(0.237)
Investment substitution effect	GSCI Energy			-0.405***	-0.388***
				(0.050)	(0.049)
	Gold Bullion			-0.448***	-0.471***
				(0.090)	(0.081)
Uncertainty effect	US EPU				-0.014*
					(0.007)
	US VIX				0.070***
					(0.026)
Adj. R^2		0.354	0.437	0.525	0.522

Notes: The standard errors are reported in parentheses. *, **, *** denote the significance at the 10%, 5% and 1% levels.

Table 9. Determinants of dynamic total connectedness for positive returns

Coefficient		Model 1	Model 2	Model 3	Model 4
Constant		-0.155**	-4.315***	-8.551***	-8.485***
		(0.062)	(1.140)	(0.987)	(0.995)
Magnitude effect	Volume (Bitcoin)	0.037***	0.021***	---	---
		(0.007)	(0.008)		
	Volume (Ethereum)	-0.010***	-0.013***	-0.010***	-0.008***
		(0.003)	(0.003)	(0.003)	(0.003)
	Volume (Ripple)	-0.021***	-0.020***	-0.009***	-0.013***
		(0.003)	(0.003)	(0.003)	(0.004)
	Volume (Litecoin)	0.022***	0.027***	0.016***	0.017***
		(0.004)	(0.004)	(0.004)	(0.004)
	Volume (Stellar)	-0.009***	-0.010***	-0.011***	-0.007*
		(0.003)	(0.004)	(0.003)	(0.004)
	Volume (Dash)	---	---	-0.007***	-0.007***
				(0.003)	(0.003)
Global financial effect	GFSI		0.020***	0.050***	0.061***
			(0.006)	(0.005)	(0.007)
	MSCI World		0.596***	2.031***	2.063***
			(0.163)	(0.154)	(0.157)
Investment substitution effect	GSCI Energy			-0.365***	-0.354***
				(0.037)	(0.038)
	Gold Bullion			-0.538***	-0.570***
				(0.062)	(0.064)
Uncertainty effect	US EPU				-0.006*
					(0.005)
	US VIX				-0.049***
					(0.021)
Adj. R^2		0.208	0.224	0.404	0.410

Notes: See notes to Table 8.

Table 10. Determinants of dynamic total connectedness for negative returns

Coefficient		Model 1	Model 2	Model 3	Model 4
Constant		-0.920**	-18.720***	-22.870***	-21.858***
		(0.095)	(1.446)	(1.495)	(1.485)
Magnitude effect	Volume (Bitcoin)	0.074***	0.012	0.031***	0.022***
		(0.010)	(0.009)	(0.010)	(0.008)
	Volume (Ethereum)		-0.021***	-0.025***	-0.033***
		---	(0.005)	(0.004)	(0.005)
	Volume (Ripple)	-0.010**	---	-0.012**	---
		(0.005)		(0.005)	
	Volume (Litecoin)	-0.014**	---	---	---
		(0.006)			
	Volume (Stellar)	0.034***	0.012**	---	---
		(0.005)	(0.005)		
	Volume (Dash)	-0.013***	-0.006	-0.010**	-0.008**
		(0.004)	(0.004)	(0.004)	(0.004)
Global financial effect	GFSI		0.058***	0.057***	0.029***
			(0.008)	(0.008)	(0.010)
	MSCI World		2.566***	3.200***	3.010***
			(0.207)	(0.250)	(0.249)
Investment substitution	GSCI Energy			-0.384***	-0.354***
effect				(0.054)	(0.050)
	Gold Bullion			0.257***	0.255***
				(0.096)	(0.080)
Uncertainty effect	US EPU				-0.021***
					(0.008)
	US VIX				0.129***
					(0.027)
Adj. R^2		0.589	0.680	0.704	0.714

Notes: See notes to Table 8.

Table 11. Determinants of dynamic total connectedness for volatility

Coefficient		Model 1	Model 2	Model 3	Model 4
Constant		-1.201**	-11.924***	-13.358***	-13.091***
		(0.092)	(1.534)	(1.526)	(1.463)
Magnitude effect	Volume (Bitcoin)	0.136***	0.093***	0.064***	0.061***
		(0.010)	(0.011)	(0.011)	(0.011)
	Volume (Ethereum)	0.006	-0.002	0.002	
		(0.005)	(0.005)	(0.005)	
	Volume (Ripple)	-0.063**	-0.062***	-0.040***	-0.028***
		(0.004)	(0.004)	(0.005)	(0.005)
	Volume (Litecoin)	-0.006	0.006	-0.005	-0.010*
		(0.005)	(0.006)	(0.006)	(0.005)
	Volume (Stellar)	0.010**	0.011*	0.012**	---
		(0.005)	(0.006)	(0.005)	
	Volume (Dash)	-0.007*	-0.005	-0.009**	-0.010***
		(0.004)	(0.004)	(0.004)	(0.003)
Global financial effect	GFSI		0.054***	0.085***	0.046***
			(0.220)	(0.008)	(0.010)
	MSCI World		1.536***	2.647***	2.495***
			(0.220)	(0.251)	(0.247)
Investment substitution effect	GSCI Energy			-0.132***	-0.159***
				(0.054)	(0.053)
	Gold Bullion			-0.801***	-0.713***
				(0.097)	(0.094)
Uncertainty effect	US EPU				0.009
					(0.007)
	US VIX				0.156***
					(0.027)
Adj. R^2		0.625	0.655	0.698	0.714

Notes: See notes to Table 8.

Regarding global financial effect, which represents global financial stress and world equities, it has a positively significant effect on cryptocurrency's market connectedness for both returns and volatility. The finding is consistent with existing literature as the cryptocurrency market still lacks transparency and the major traders are young and inexperienced individual investors[16].There are dispersion of information and uncertainty among crypto traders (Bouri et al., 2018b). Indeed, the extreme speculative nature of the Bitcoin makes the cryptocurrency markets highly

[16] Generally, individual investors rely on social media and online chat forums for information content about the cryptocurrencies.

volatile, which may encourage herding behaviour in Bitcoin market (Baur et al., 2018)[17]. There is also evidence that herding behaviour tends to occur and intensify during financial stress periods (Demirer and Kutan, 2006).

U.S. EPU and energy prices have a negative effect, and that regardless of the type of returns considered. The finding is in line with existing literature, where Demir et al., (2018) found evidence that U.S. EPU index has predictive power on Bitcoin returns, and Bitcoins returns are negatively correlated with the U.S. EPU. Therefore, Bitcoin can serve as a hedging tool against EPU.

However, the picture is different for the explanatory role of gold prices, energy price, and US VIX. Gold prices and Energy prices have a negatively significant effect when considering aggregate- and positive-return spillovers, whereas US VIX exhibits a positive effect in aggregate- and negative-return spillovers. The finding is not surprising as Bitcoin possess some of the same hedging ability as gold (Dyhrberg, 2016). As a substitute to Bitcoin, an increase in gold price will decrease demand for cryptocurrency, and therefore weaken the return connectedness of return spillover for the cryptocurrency market. Furthermore, it has been documented in the literature that an inverse relationship exists between the US stock market uncertainty (as measured by the VIX) and the Bitcoin volatility, implying that, in an environment of high uncertainty in the stock market, market participants can move into Bitcoin to hedge any possible stock market losses (Bouri et al., 2017a, b). In our case, the hedge effect occurs in cryptocurrency market, making its returns connectedness stronger for aggregate- and negative-return spillovers. In conclusion, the magnitude of the effect, as measured by the level of the coefficient associated with the explanatory variables, indicates that world equities, energy and gold prices are the most influential on cryptocurrency integration, with some nuanced differences between negative- and positive-return spillovers.

As for the determinants of the net pairwise directional-volatility spillovers (Table 11), it is interesting to see that not every cryptocurrency's volume is

[17] It has been found in the literature that herding could intensify the volatility of asset class and make the financial system unstable (Demirer and Kutan, 2006).

significant, and that US EPU has no effect. In contrast, global financial stress, world equities and US VIX have a positively significant effect, whereas energy and gold prices exhibit a negative effect. These results are quite similar to that reported for the determinants of dynamic total connectedness for returns (Table 8), suggesting that the same factors (global financial effect, investment-substitution effect and US VIX) drive both return and volatility spillovers in the cryptocurrency market.

4. Conclusions

This study contributes to the growing empirical literature on the cryptocurrency market by quantifying for the first time spillover effects across six large cryptocurrencies in order to better understand the spillover nature of each cryptocurrency. By applying the connectedness framework of Diebold and Yilmaz (2012, 2016) on daily data, we built positive and negative returns-connectedness and volatility-connectedness networks. The empirical results show that, in addition to the largest cryptocurrency (Bitcoin), a relatively smaller one (Litecoin) is at the centre of returns and volatility connectedness, sharing with Bitcoin the dominant transmitting role to total return and volatility spillovers.

Interestingly, the second-largest cryptocurrency (Ethereum) is a recipient of spillovers and is thus quite dominated by both larger and smaller cryptocurrencies. Although these results confirm the findings of Corbet et al. (2018) that leading cryptocurrencies are interconnected, they differ in finding that Litecoin has significant influence on Bitcoin as well as on other leading cryptocurrencies. This finding suggests that Bitcoin is losing its dominant role in the evolving cryptocurrency market. All cryptocurrencies are found to alternate between being transmitters and receivers, depending on the time. Asymmetries in negative-return spillovers are significant and have a more substantial magnitude than in positive-return spillovers, implying that negative returns materialize quite frequently and that their magnitudes are not lessened by positive-return spillovers.

Regression analyses show that the drivers of the integration degree of the cryptocurrency-market system are affected by a diverse set of variables. Overall, the results point to the importance of trading volume, the global and investment-substitution effect and the uncertainty effect to the determination of the net directional spillover among cryptocurrencies returns. This finding is not surprising and partially concords with prior studies that highlight the importance of trading volume (Balcilar et al., 2017), US stock-market volatility (Bouri et al., 2017a & b) and economic policy uncertainty (Demir et al., 2018).

The interdependency across the largest cryptocurrencies and its determinants affect the decision-making of investors, policy-makers and scholars. It is interesting to know that, overall, large cryptocurrencies exhibit relatively diverse levels of integration and that, consequently, shocks to one cryptocurrency do not generally induce large spillovers to the other segments in a way that would reduce diversification possibilities. In fact, crypto-investors may benefit from some evidence of weak integration in some cases (e.g., Dash) to improve their portfolio diversification by exploiting the findings on how cryptocurrencies' returns influence one another, while differentiating between positive and negative returns. As for the results of volatility connectedness, they can assist crypto-investors in building volatility-hedging strategies and consistently managing risk via measures such as value-at-risk.

As the cryptocurrency market evolves and matures, it is of particular interest to policy-makers and investors to extend our analysis by constructing a diversified cryptocurrency portfolio that maximizes return and balances risk while accounting for the risk preferences of crypto-investors.

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APPENDIX

Table A.1. Explanatory variables of spillovers

Variable	**Description**
Trading volume	Trading volume on each of the leading cryptocurrencies under study
GFSI	Bank of America Merrill Lynch's Global Financial Stress Index
MSCI World	Morgan Stanley Capital International World index. It represents large- and mid-cap equity performance across 23 developed-market countries
GSCI Energy	The S&P Goldman Sachs Commodity Energy Index Spot
Gold Bullion	The spot price of one ounce of gold
US EPU	The news-based US Economic Policy Uncertainty Index
US VIX	The CBOE US Implied Volatility Index, which measures 30-day expected volatility conveyed by S&P 500 Index option prices